AN AUTOMATIC APPROACH FOR PARAMETER SELECTION IN SELF-ADAPTIVE TRACKING

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Abstract: In this article we propose an automatic approach for parameter selection of a tracking system. We show that such a self-adaptive tracking system achieves better tracking performance than a system with manually tuned parameters. Our approach requires little supervision by a user which makes this approach ideally suited for commercial applications. The self-adaptive component makes the system less sensitive to changing environmental conditions. Components for tracking, auto-critical evaluation and automatic parameter regulation serve to detect performance drops that trigger the parameter regulation process. The self-adaptive components require a quality measure based on a statistical scene reference model. We propose an automatic approach for the generation of such a reference model and compare several learning approaches. The experiments show that the auto-regulation of parameters significantly enhances the performance of the tracking system.

1 INTRODUCTION

In this article we propose an automatic approach for parameter selection of a tracking system. We show that such a self-adaptive tracking system achieves better tracking performance than a system with manually tuned parameters. Our approach requires little supervision by a user during initialisation which makes this approach ideally suited for commercial applications.

The future goal of this work is to incorporate the technology of self-adaptation into commercial video surveillance systems. The growing number of installed video surveillance systems represent a great demand for automatic setup and configuration. Nowadays, an engineer is required for system installation. The installation requires also the manual adaptation of parameters. Such systems perform well as long as the environment stays constant. Unfortunately, in most real applications the environmental conditions perceived by the sensors frequently change, which often breaks the system and requires reinitialisation and new hand tuning of the parameters. For a company with a large number of systems, the maintenance including manual parameter tuning would require too much resources. This article proposes an approach that makes hand tuning of parameters obsolete. The approach is automatic that means it requires no human supervision during run time, human supervision is required only for the initialisation of the model generation.

Our approach generates a scene reference model that models correct system output in a probabilistic manner. Based on this model we define a metric to judge the system output (detect errors and detect performance decrease). This metric is also used to select the optimal parameter setting for the current environmental conditions. The selection is automatic without prior knowledge about the environmental condition change.

In this article we address the important steps of our approach. First, generation of the scene reference model and model selection. Second, definition of a quality metric and third, development of a strategy for parameter space exploration.

As related work we want to cite Murino who addresses the problem of automatic parameter regulation for vision systems in (Murino et al., 1996). He proposes a multi-layered component architecture. Each layer has its own set of parameters that are tuned such that the evidence (coming from the lower level) and the expectation (coming from the higher level) are consistent. The improvements are not convincing and the approach lacks the use of an external knowledge base.

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Scotti (Scotti et al., 2003) proposes an approach based on self organizing maps (SOM). The SOM is learnt by registering good parameter settings. During run time, the automatic parameter selection chooses the closest setting in SOM space that performed best during training. The experiments are not convincing and we think that the method has strong limitations.

In (Min et al., 2004), Min proposes an approach for comparing the performance of different segmentation algorithms by searching the optimal parameters for each algorithm. He proposes an interesting multi-loci hill climbing scheme on a coarsely sampled parameter space. The segmentation system performance is evaluated with respect to a given ground truth. This approach is designed for the comparison of algorithms and requires to test a large number of different parameter settings. For this reason, the utility of this approach for on-line parameter regulation is less appropriate.

The remainder of the article is organised as follows. Section 2 describes the components of the self-adaptive system architecture. The self-adaptive components depend on a quality metric described in section 3. Section 4 describes experiments in which we test the self-adaptive capabilities of our system. We finish with an overview and an outlook on how this kind of system could be used in commercial applications.

2 ARCHITECTURE OF A SELF-ADAPTIVE TRACKING SYSTEM

In this section, we propose an architecture for a self-adaptive tracking system. We first discuss the architecture and then describe the individual components.

Commercial use of automatic parameter tuning has very strong requirements on the method. First, the method should reduce user interaction to a minimum and second, parameter tuning should not slow down tracking of the master system. This architecture separates the master system from the self-adaptive component which makes it suited for an implementation on a distributed system. The tracking system with the fast monitoring component can run on one host and the costly parameter tuning process can run on a second host while the master system continues tracking.

2.1 Self-adaptive Systems

Robertson and Brady (Robertson and Brady, 1999) propose an architecture for self-adaptive systems. They consider an image analysis system as a closed-loop control system that integrates knowledge in or-

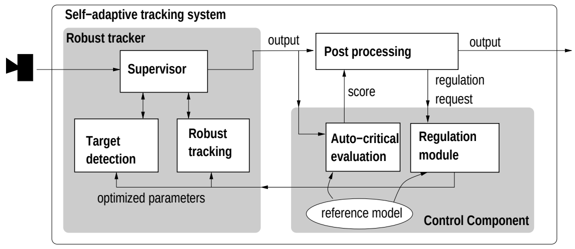


Figure 1: Architecture of a self-adaptive tracking system.

der to be self-evaluating. Measuring and comparing the system output to the desired output and applying a corrective force to the system leads to increased performance. The difficult point is to generate a model of the desired output. They demonstrate their approach on the segmentation of aerial images using a bank of different filter operators. The system selects automatically the best filter for the current image conditions.

We follow this line of research and design a self-adaptive system with a control component. The control component implements following abilities:

- Auto-critical evaluation: This means that the system is able to judge its own performance.
- Auto-regulation of parameters: The ability to automatically adapt the system's parameters to the current environmental conditions and ensure constant performance.

2.2 System Architecture

Figure 1 shows the architecture of the self-adaptive tracking system containing a tracking system and an independent control component. The independence of the control component allows to endow other types of perceptual systems with self-adaptive capabilities in a plug-and-play manner.

The above abilities of auto-critical evaluation and auto-regulation are implemented as modules within the control component. The output of the perceptual system is monitored by the module for auto-critical evaluation. Auto-regulation is triggered by an external request from the post processing module. The modules have access to a common knowledge base that contains the reference model.

The structure and content of this knowledge base is task dependent. This means that each system setup requires a knowledge base with different structure and different content. Section 3 explains in detail how this knowledge base can be generated automatically in the context of a robust tracking system.

2.3 Robust Real-time Tracking

This self-adaptive architecture is applied to a real-time tracking system in a video surveillance scenario.

The tracking system is composed of a central supervisor that calls in a cycle the modules video demon, automatic target detection and robust tracking. The supervisor manages the list of current targets. The tracking module provides robust tracking of the current targets using a Kalman filter. The detection module based on adaptive background differencing detects new targets that are added to the target list. The system can track up to 8 targets in images of 384×288 pixels at 30Hz on a 2 GHz processor.

The robust tracking system produces for each frame t_i and each target a vector (measurement) composed of centroid and width and height of the target's bounding box $\vec{y}(t_i) = (x_c, y_c, w, h)^T$. These vectors are summarised in a log file in XML format. The tracking result depends on a number of parameters such as detection energy threshold (minimum target size), noise threshold (pixel energy below this threshold is considered as noise) and parameters that control split and merge of targets. These parameters determine how close targets need to be for fusion or separation. For further details on the system implementation see (Caporossi et al., 2004).

2.4 Auto-critical Evaluation

The goal of the auto-critical evaluation is to monitor the performance of the system and detect performance drops. This requires the definition of a measure that estimates the goodness of trajectories (measurement sequences) with respect to a reference model that is constructed in a learning phase. Such a reference model describes what usually happens in the scene. An example of a different reference model is the semantic scene model of Makris and Ellis in (Makris and Ellis, 2003) where they learn entry and exit points from examples and represent them as a Gaussian mixture. Trajectories are represented by a topological graph.

There is a wide range of different representation forms of reference models. In addition to graphs and Gaussian Mixture Models (GMMs), we want to name histograms that often provide a good solution to concrete problems despite their simplicity. Probability density approximations such as histograms or GMMs have the advantage that a goodness score can be defined easily based on statistical estimation.

All probabilistic reference models have in common that they estimate the true probability density function (pdf) of measurements $\vec{y} = (x_c, y_c, w, h)^T$. For example a pdf represented by a GMM can be obtained by applying a standard learning approach such as clustering to the training data and representing each cluster by a Gaussian. In that case, the probability density of a d dimensional measurement $\vec{y}$ is computed by

$$p(\vec{y}) = \sum_{j=1}^{K} p(\vec{y}|C_j)P(C_j) \tag{1}$$

$$p(\vec{y}|C_j) = p(\vec{y}|\vec{\mu_j}, U_j) = \frac{1}{(2\pi)^{d/2}|U|^{1/2}} e^{(-0.5(\vec{y}-\vec{\mu_j})^T U^{-1}(\vec{y}-\vec{\mu_j}))} \tag{2}$$

with $\vec{\mu_j}$ mean and U_j covariance of Gaussian C_j. The priors $P(C_j)$ are estimated from the training data:

$$P(C_j) \approx \frac{|C_j|}{M} \tag{3}$$

with $|C_j|$ number of data points associated to C_j during training and M total number of data points used for training.

Equation 1 provides the probability density of single measurements. To compute the quality of a trajectory, we average the probability of the single measurements. The goodness $G_{avg}(y(t))$ of the trajectory $y(t) = (\vec{y}_n, \ldots, \vec{y}_0)$ with length $n+1$ is computed as follows:

$$G_{avg}(y(t)) = \frac{1}{n+1} \sum_{i=0}^{n} p(\vec{y}_i) \tag{4}$$

using eq 1 for computing $p(\vec{y}_i)$. We have tested two other goodness measures (see (Hall, 2005)), but the simple averaging technique provided the best results.

This monitoring component is able to detect errors and global performance drops automatically by evaluating the goodness score of the system output.

2.5 Automatic Parameter Regulation

The goal of the regulation module is to find a parameter setting that increases the system performance. In the current implementation, this requires the simulation of tracking output using different parameter settings. Depending on the number of tested parameter settings, this task is time consuming. In a real-time commercial application, the tracking application and the parameter regulation can be run in parallel on a distributed system.

The module architecture is illustrated in Figure 2. Parameter regulation is started by a request from the post processing module in cases where a performance drop is detected. The request contains the current parameter setting and an image sequence composed of the last k frames. The regulation tool searches now for a parameter setting that has good performance on this sample sequence. The parameter space exploration tool provides new parameter settings. Feedback of the goodness of previous parameter settings may be used to guide the search. The tracking system simulator simulates the output of the tracking system on the sample sequence with these parameter settings.

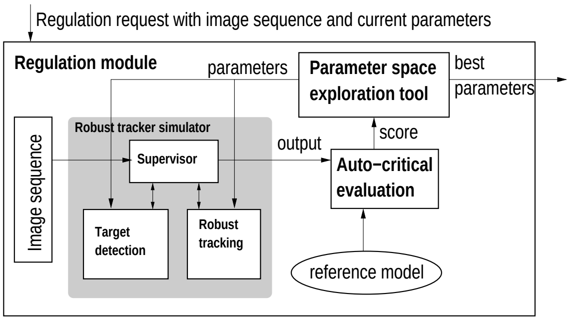


Figure 2: Architecture of the automatic parameter regulation module.

The goodness score for the output is computed by the auto-critical evaluation. Ideally, the parameter regulation continues until it finds a parameter setting that repairs the failure (this means that the performance must exceed a predefined acceptance threshold). In the experiments, auto-regulation of the parameters is performed on the entire sequence. The current implementation tests a maximum number of parameter settings and returns the one with the best performance.

The parameter regulation module contains an independent module for parameter space exploration. This allows to test different exploration strategies. We tested an enumerative strategy and a strategy based on a genetic algorithm. Gradient based methods or adaptive sampling as in (Min et al., 2004) could also be used.

3 GENERATION OF A SCENE REFERENCE MODEL

The scene reference model together with a quality metric forms the knowledge base of the self-adaptive system. It allows the system to judge the quality of the system output and to select parameters that are optimal with respect to this metric. The success of the self-adaptive technique depends on the representativeness of this scene reference model and its metric. As a consequence, model generation is an important step within this approach.

With respect to commercial applications and the fact that only a limited number of ground truth data may be available for initialisation, we focus especially on model representation forms and learning techniques that are incremental. Such techniques have the great advantage, that they can be refined as more data becomes available.

In this section, we explain different model generation methods. All methods operate on the same 4 dimensional training data of the form $\vec{y} = (x_c, y_c, w, h)^T$ and provide an estimation of the underlying pdf.

3.1 Learning Methods for Model Generation

We tested several incremental and non-incremental methods for model generation from hand-labelled training data. The most interesting methods for which we show experimental results are:

- non incremental methods like kmeans with pruning (*KM-F*) and EM with pruning (*EM-F*),
- incremental method based on a multi-dimensional histogram *Histo*,
- the incremental method *Histo-EM-F* consists in building a fine grain histogram, extracting a weighted point for each non empty cell and then performing EM with pruning on the extracted points. The histogram serves to obtain an intermediate representation of the data and to reduce the number of points considered for EM.

The current implementation requires hand labelled data for model construction. In a future version, we envision an iterative learning scheme that generates an initial model from little hand labelled data (a few trajectories). This model would then be used to filter the output of the tracking system to obtain more correct data. An improved model would then be learnt from the enhanced set of training data. Several iterations of this scheme should produce a high quality model.

In such an iterative learning scheme, an incremental model structure has several advantages. Incremental algorithms have the advantage of being able to refine the model subsequently while new observations arrive. Incremental models can incorporate very large amounts of data, because training data from previous iterations does not need to be stored. For this reason, incremental learning schemes should be able to produce higher quality models than non-incremental learning schemes.

3.2 Reference Model Selection

The above methods have several parameters such as the number of Gaussians in the GMM that can not be determined a priori. A successful strategy for finding a model of high quality is to generate a large set of models by varying the parameters of the methods and then selecting the best model with respect to some quality criterion. We propose to use a quality criterion based on the probability of classification error with respect to a validation set of positive and negative measurements. Section 4 describes how such a validation set can be acquired.

For each model, a classifier is built by selecting a threshold on the probability density $p(\vec{y})$ of the measurements $\vec{y}$. Given the validations sets Pos and Neg of positive and negative examples, the threshold is chosen automatically as the value that minimise the probability of classification error:

$$P_{err} = \frac{1}{|Pos| + |Neg|} \min_{th} \left(\sum_{p \in Pos} \delta_{pdf(p)<th} + \sum_{n \in Neg} \delta_{pdf(n) \geq th} \right) \quad (5)$$

where δ is the Kronecker symbol. The least complex model with a P_{err} value below an acceptance threshold is said to have the best quality. This quality measure based on P_{err} is an efficient way of selecting the model.

The complexity of a model is related to the number of Gaussians or the the number of histogram cells (depending on the representation). Selecting the least complex model that fulfils an acceptance threshold is a regularisation method that avoids over fitting. The acceptance threshold is determined experimentally (see Section 4).

4 EXPERIMENTAL EVALUATION

In the experiments we want to demonstrate three points: i) the quality of the automatic parameter selection, ii) the performance increase of tracking by auto-regulation of parameters compared to manual parameter tuning and iii) the link between the model quality measure P_{err} and the system performance.

4.1 Performance Evaluation

For measuring the performance of our tracking system, we measure recall and precision. These values are computed by a statistics tool that operates on XML description of the bounding boxes of the detected targets and of the manually annotated targets. The statistics tool determines for each frame the best matching pairs with respect to overlap of detected and ground truth boxes. For a particular overlap threshold T, the tool evaluates the number of true positives (TP), false positives (FP) and false negatives (FN).

$$\text{Recall} = \frac{\text{TP}}{\text{TP + FN}} \qquad \text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (6)$$

The overlap of two bounding boxes is computed by:

$$O(A_{obs}, A_{truth}) = \frac{\lambda\{A_{obs} \cap A_{truth}\}}{\lambda\{A_{obs} \cup A_{truth}\}} \quad (7)$$

where $\lambda\{\ldots\}$ represents the surface (Lebesgue measure in dimension 2) and A the bounding box.

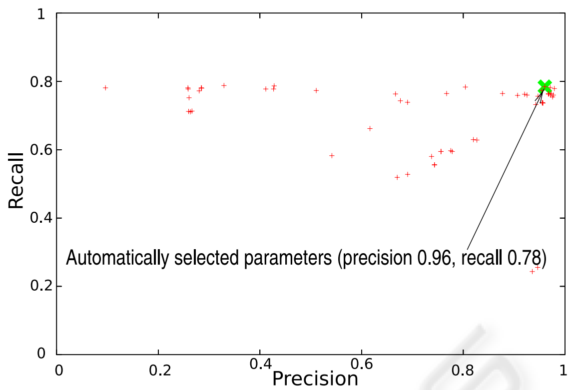


Figure 3: Evaluation of the quality of automatically selected parameters. Our automatic approach selects a parameter setting among those with best performance.

In addition we compute the area under the curve (AUC) for Recall and Precision as in (Min et al., 2004). The AUC is a comparison measure that is independent of a particular overlap threshold. A perfect system would have AUC of 1.0.

4.2 Results and Interpretation

The experiments are evaluated on public benchmark data (Fisher, 2004). These are 27 video sequences with hand labelled ground truth data. We divided this set in 13 sequences for training (18411 bounding boxes) and 14 sequences for testing (21217 boxes).

Quality of the automatic parameter regulation
This experiment gives insight in the quality of the automatically selected parameter setting using our approach. For given sequence, our approach selects a parameter setting using a search strategy by a genetic algorithm. For parameter selection we use the generated scene reference model with the metric $G_{avg}(y(t))$. This parameter setting is then used to generate an output in XML format. The statistics tool provides values for recall and precision for an overlap threshold of $T = 0.5$. This recall/precision pair is represented as a point in the precision recall plot of Figure 3.

To demonstrate the quality of this result, we compare it to the precision recall values of a large number of different parameter settings (all parameter settings that are selected by the genetic algorithm, 3 generations of 20 individuals). Figure 3 shows clearly, that the automatically selected parameter setting is among the settings with the best performance. For other sequences we observe a similar behaviour.

Performance increase by auto-regulation
We measure the performance of the tracking system

Table 1: Performance (on 14 sequences) of self-adaptive tracking and benchmarks.

Method	AUC_{recall}	$AUC_{precision}$
Manual tuning (on 6 sequences)	0.429	0.532
Auto-regulation using KM-F (batch)	0.437	0.629
Auto-regulation using Histo-EM-F	0.431	0.648
No regulation (low thresholds)	0.414	0.391
No regulation (high thresholds)	0.243	0.426

by evaluating the output of the system that uses the parameter setting chosen by the auto-regulation algorithm. Table 1 shows the results of the different methods on the 14 test sequences. The auto-regulation methods are compared to three benchmarks. The upper benchmark is our tracking system with manually tuned parameters. We only have the results for 6 test sequences due to the tedious manual task. The lower benchmarks are provided by using static parameter settings for all test sequences. Low thresholds give good recall but bad precision, high thresholds give bad recall and bad precision.

We compare the auto-regulation method using a batch model *KM-F* and the best performing incremental method *Histo-EM-F*. The *KM-F* model is obtained using a KMeans clustering with 1000 initial clusters that are subsequently merged. All clustering solutions from 100 to 5 clusters are transformed to a GMM. The model obtained by the method *Histo-EM-F* uses a fine grain histogram for initialisation of EM. The Gaussians computed by EM are subsequently merged to provide a fusion tree. In both methods, we choose the least complex model with a P_{err} value below the acceptance threshold of 5% (see paragraph below).

The incremental model and the batch model both match the performance of a manually tuned system (although the manually tuned system is evaluated only on 6 sequences, the AUC values give an idea of the performance range). The increase in performance using automatic parameter regulation with respect to using no regulation is demonstrated clearly by the comparison to the lower benchmark performance. Another important result is that no significant difference can be noted between the incremental and non-incremental model. This motivates the use of incremental models in the future due to their ability of further refinement with additional data.

Link between P_{err} and tracking performance

In section 3.2 we proposed a measure for model selection based on the probability of classification error. This is a convenient and fast measure for model selection. The definition and validation of such a fast quality measure makes possible the automatic generation and selection of a scene reference model in a non-supervised commercial tracking application. For validation of this measure, we need to show the relation between P_{err} and the tracking performance.

We perform following experiment. 4 sequences are selected among the test sequences with different degree of difficulty (1 easy, 2 intermediate and 1 hard). We compute the P_{err} scores for a family of models extracted from different levels of the fusion tree produced by the *GNGN-EM-F* approach (a growing neural gas network (Fritzke, 1995) is used for initialisation of EM with fusion). P_{err} requires the selection of a representative set of positive and negative examples. The positive examples are composed of 7 trajectories of the most common paths of the scene (2420 measurements). The negative examples are obtained by monitoring the tracking output and collecting tracking errors (1997 measurements). Each model is then used for auto-regulation of parameters. The XML output of the tracking system using the selected parameter setting is evaluated and the AUC values of precision and recall are computed.

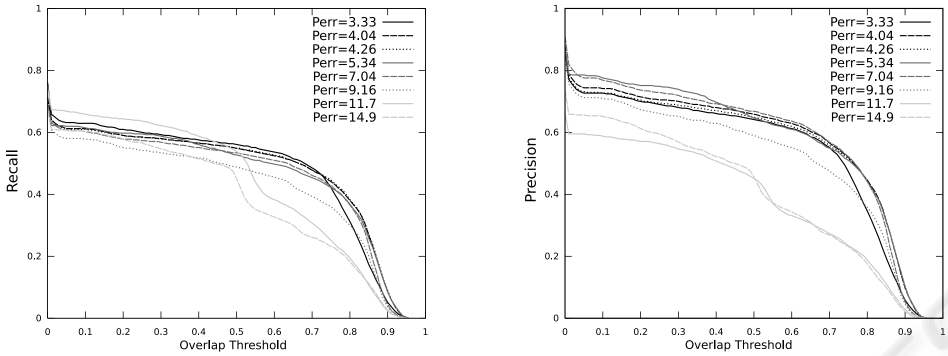
Table 2 shows these results. The results confirm the relation between the P_{err} value and the global performance of the system using auto-regulation. Small P_{err} values (good model quality) yield good tracking performance (high precision and high recall). The results show also that no further improvement is observed for P_{err} values below 5%. We observed a similar behaviour for model families obtained by other learning approaches. The performance stabilises for P_{err} values below 5%. As a consequence, in this particular system setup, a model with a P_{err} value below 5% is appropriate for parameter regulation.

5 CONCLUSION AND OUTLOOK

We described an architecture for a self-adaptive tracking system that uses a control component to implement the abilities of auto-criticism and auto-regulation. Both modules require a metric with respect to a reference model. Our approach allows to automatically generate and select such a reference model with good quality without human supervision. The quality of the model is determined by a fast evaluation measure based on the classification error with respect to a validation data set.

The experiments show that a tracking system with auto-regulation of parameters has the same or better performance than a tracking system with manually tuned parameters. We also demonstrate that our automatic parameter selection scheme selects parameter settings with very high performance. The exper-

Table 2: Performance (evaluated on 4 sequences) of self-adaptive system using incremental models with increasing P_{err}. Performance degrades as P_{err} increases.



P_{err} (in %)	3.33	4.04	4.26	5.34	7.04	9.16	11.7	14.9
$\text{AUC}_{\text{recall}}$	0.47	0.47	0.47	0.46	0.45	0.40	0.44	0.38
$\text{AUC}_{\text{precision}}$	0.52	0.56	0.55	0.58	0.58	0.48	0.29	0.39

iments validate the fast evaluation measure P_{err} on example sequences.

With respect to a future integration in a commercial tracking system, the result that incremental model generation produces equal results than batch model generation is important. Incremental learning techniques have the advantage that they allow subsequent refinement of the reference model without the need of storing all training data. This is a great advantage with respect to direct learning methods such as k-means clustering or EM whose computational complexity depends on the total number training data. The data required for a model with very good quality may reach quickly the upper limit of memory space and available computation time.

The next step of our work consists in developing a prototype that can be used for an automatic installation of a self-adaptive tracking system in a new site. The here proposed technique is fully automatic once the ground truth data is acquired. Hand-labelling ground truth may be replaced by a robust and reliable tracker using colour information. An initialisation phase would require the cooperation of several actors wearing coloured suits. 10 minutes of acting provides 18000 frames of example data which are sufficient for a scene reference model of a lobby with several entries and unconstrained walking paths. Following these steps, a scene reference model for a new video surveillance site can be generated automatically using the here proposed approach.

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